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A data envelopment analysis model for selecting suppliers in the presence of both dual-role factors and non-discretionary inputs

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Abstract

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Keywords

factors, dual-role, both, presence, non-discretionary, suppliers, inputs, selecting, model, analysis, envelopment, data

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Abstract: Supplier selection is the strategy adopted by the manufacturer, to evaluate and select suppliers, which can fulfil the requirements of the manufacturer. To this end, data envelopment analysis (DEA), as a multiple criteria decision-making tool, has been applied for several times. However, conventional DEA models cannot simultaneously consider dual-role and non-discretionary factors. The objective of this paper is to propose a DEA model for ranking suppliers in the presence of both dual-role factors and non-discretionary inputs. A numerical example demonstrates the application of the proposed model.

Keywords: data envelopment analysis; DEA; supplier selection; dual-role factors; non-discretionary inputs.

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1 Introduction

Most manufacturing enterprises are organised as networks of manufacturing and distribution sites that procure raw materials, transform them into intermediate and finished products, and distribute the finished products to customers (Lee and Billington, 1992). The short-term objective of supply chain management (SCM) is primarily to increase productivity and reduce the entire inventory and the total cycle time, while the long-term objective is to increase customer satisfaction, market share, and profits for all organisations in the supply chain (Tan et al., 1998). Shin et al. (2000) argue that several important factors have caused the current shift to single sourcing or a reduced supplier base. First, multiple sourcing prevents suppliers from achieving the economies of scale based on order volume and learning curve effect. Second, a multiple supplier system can be more expensive than a reduced supplier base. For instance, managing a large number of suppliers for a particular item directly increases costs, including the labour and order processing costs to managing multiple source inventories. Meanwhile multiple sourcing lowers overall quality levels because of the increased variation in incoming quality among suppliers. Third, a reduced supplier base helps eliminate mistrust between buyers and suppliers due to lack of communication. Fourth, worldwide competition forces firms to find the best suppliers in the world.

The objective of this paper is to propose a new data envelopment analysis (DEA) model for ranking suppliers in the presence of both non-discretionary inputs and dual-role factors.

DEA is proposed by Charnes et al. (1978) and provides a non-parametric methodology for evaluating the efficiency of each of a set of comparable decision-making units (DMUs), relative to one another. DEA is a non-parametric mathematical programming technique that determines an efficient frontier of the most efficient DMUs and calculates the efficiency of each DMU relative to this efficient frontier based on multiple observed inputs and outputs. An efficiency score of a DMU is generally defined as the weighted sum of outputs divided by the weighted sum of inputs, while weights need to be assigned. To avoid the potential difficulty in assigning these weights among various DMUs, a DEA model computes weights that give the highest possible relative efficiency score to a DMU while keeping the efficiency scores of all DMUs less than or equal to one under the same set of weights (Liu et al., 2000).

In DEA, DMU is evaluated against the performance of the remaining DMUs in the sample via a ratio of the sum of weighted outputs to the sum of weighted inputs. Two restrictions are applied. The first restriction is that the weights must be non-negative. The second restriction is that the weighting scheme used will be applied to all other DMUs in the sample and none of them may have a ratio greater than one. Therefore, an inefficient DMU is one for which a weighting scheme cannot be found that evaluates it better than all other DMUs. An attempt is made to find the weighting scheme for each DMU that casts it in the most favourable light possible and the resulting ratio is designated the DMU's efficiency value (Anderson et al., 2002). In DEA formulations, the assessed DMUs can freely choose the weights or values to be assigned to each input and output in a way that maximises its efficiency, subject to this system of weights being feasible for all other DMUs. This freedom of choice shows the DMU in the best possible light, and is equivalent to assuming that no input or output is more important than any other. The free imputation of input-output values can be seen as an advantage, especially as far as the identification of inefficiency is concerned. If a DMU (supplier) is free to choose its own value system and some other suppliers uses this same value system to show that the first supplier is not efficient, then a stronger statement is being made. The primary problem associated with arbitrary weights (which is mostly used in MCDM methods) is that they are subjective, and it is often a difficult task for the decision-maker (DM) to accurately assign numbers to preferences. It is a daunting task for the DM to assess weighting information as the number of performance criteria increased. DEA does not demand exact weights from the DM. Since classical techniques always require intuitive judgements that have biases, DEA helps DMs to select the suppliers without relying on intuitive judgements (Farzipoor Saen, 2010b).

In applying DEA, there is a strong argument for permitting certain factors to simultaneously play the role of both inputs and outputs. Such factors such as suppliers research and development (R&D) cost clearly constitute an output measure, but at the same time it is an important component of the supplier, hence, it is an input. From the perspective of DM who intends to select the best supplier, such measures may play the role of proxy for 'suppliers' innovation'. R&D results in the technology that brings new products and services to the market place or strengthens better processes. Innovation results in high quality jobs, successful businesses, better goods and services and more efficient processes. That is why R&D can reasonably be classified as output. On the other hand, from the perspective of supplier, it can be considered as input that imposes special expenses to the supplier.

On the other hand, discretionary models for evaluating the efficiency of suppliers assume that all criteria are discretionary, i.e., controlled by the management of each supplier and varied at its discretion. Thus, failure of a supplier to produce maximal output levels with minimal input consumption results in a decreased efficiency score. In any realistic situation, however, there may exist exogenously fixed or non-discretionary criteria that are beyond the control of a management. For example, consider suppliers distance from the factory which is an input. It will not be acceptable from the supplier's perspective to decrease the distance in order to improve its performance.

Clearly, there may exist a situation that these two factors (i.e., the dual-role factors and non-discretionary inputs) should be considered simultaneously and a technique that can deal with these two factors in a single model is needed to better model such situation.

Another issue which has been discussed frequently in the suppliers ranking literature has been the lack of discrimination in DEA applications, in particular when the number of inputs and outputs is too high relative to the number of DMUs. The basic DEA models classify the DMUs into two groups, efficient and inefficient. Often DMs are interested in a complete ranking in order to refine the evaluation of the units. To this end, we use 'virtual best' DMU concept to derive the complete ranking of suppliers.

This paper proceeds as follows. In Section 2, literature review is presented. Section 3 introduces the method which ranks the suppliers in the presence of both dual-role factors and non-discretionary inputs. Numerical example and concluding remarks are discussed in Sections 4 and 5, respectively.

2 Literature review

2.1 Supplier selection

Some mathematical programming approaches have been used for supplier selection in the past. Nydick and Hill (1992), Barbarosoglu and Yazgac (1997), and Narasimhan (1983) used analytic hierarchy process (AHP) to support supplier selection decisions. Akarte et al. (2001) developed a web-based AHP system to evaluate the casting suppliers with respect to 18 criteria. In this system, suppliers should first register, and then input their casting specifications. To evaluate the suppliers, buyers determine the relative importance weightings for the criteria based on the casting specifications, and then assign the performance rating for each criterion using a pairwise comparison. Chan (2003) developed an interactive selection model with AHP to facilitate DMs in selecting suppliers. Kahraman et al. (2003) suggested fuzzy AHP for selecting the best supplier providing the most satisfaction for the determined criteria. Ghodsypour and O'Brien (1998) used AHP and linear programming to select suppliers.

Sarkis and Talluri (2002) believe that supplier evaluation factors would influence each other, and the internal interdependency need to be considered in the evaluation process. The authors applied analytic network process (ANP) to evaluate and select the best supplier with respect to organisational factors and strategic performance metrics, which consist of seven evaluating criteria.

Lee (2008) proposed a mean-variance approach to determine the optimal number of suppliers in the presence of supplier failure risks. The mean value approach assumes that the firm has a linear utility function with respect to the supply disruptions. Hu and Xie (2010) considered the value of practicing early order commitment (EOC) in a supply chain with demand uncertainty and lost sales. They also examined the impact of forecasting errors and inventory policies used by the retailers on the performance of the supply chain. Xiao et al. (2010) developed a two-period game model of a supply chain consisting of one manufacturer and one retailer to investigate the pricing and effort investment decisions when customer satisfaction is considered. Dharmapala (2008) used the DEA model with intrinsic assurance regions (IAR) and focused on how to make cost savings in a supply chain by projecting inefficient supply units on to the efficient frontier.

Choy and Lee (2002) proposed a generic model using the case-based reasoning (CBR) technique for supplier selection. Various evaluating criteria were grouped into three categories: technical capability, quality system, and organisational profile. The model was implemented in a consumer products manufacturing company, which had stored the performance of past suppliers and their attributes in a database system. Choy et al. (2005) applied the CBR-based model to aid DMs in the supplier selection problem.

Lin and Chen (2004) presented a fuzzy decision-making framework for selecting the most favourable strategic supply chain alliance under limited evaluation resources. Holt (1998) and Li et al. (1997) applied fuzzy sets theory in supplier selection. Sarkar and Mohapatra (2006) suggested that performance and capability are two major measures in the supplier evaluation and selection problem. The authors used the fuzzy set approach to account for the imprecision involved in numerous subjective characteristics of suppliers. A hypothetical case was adopted to illustrate how the two best suppliers were selected with respect to four performance-based and ten capability-based factors. Talluri and Baker (2002) developed a binary integer linear programming model to evaluate alternative supplier bids based on ideal targets for bid attributes set by the buyer, and to select an optimal set of bids by matching demand and capacity constraints. Based on four variations of model, effective negotiation strategies were proposed for unselected bids.

Karpak et al. (2001) constructed a goal programming (GP) model to evaluate and select the best suppliers. Three goals were considered in the model, including cost, quality, and delivery reliability. Wadhwa and Ravindran (2007) modelled the supplier selection problem as a multi-objective programming (MOP) problem, in which there are three objective functions, such as minimisation of price, lead time, and rejects. Three solution approaches, including weighted objective method, GP method, and compromise programming were used to compare the solutions. Vokurka et al. (1996) proposed to incorporate expert system technology into a decision-support framework. Their expert system integrates the judgement and expertise of purchasing professionals with the formal approaches of earlier works. Ndubisi et al. (2005) used a multiple regression model for supplier selection and found that the selection of supplier based on technology is important for the manufacturer whose focus is on product and launch flexibility. Rezaei and Davoodi (2008) considered the problem of supply chain with multiple suppliers and multiple products. Their supplier evaluation includes four major assumptions:

a suppliers have limited capacity

b received items from suppliers are not of perfect quality

c the demand over a finite planning horizon is known d the buyer has a maximum storage space in each period.

Weber (1996) applied DEA in supplier evaluation for an individual product and demonstrated the advantages of applying DEA to such a system. In this study, the criteria for selecting suppliers were significant reductions in costs, late deliveries and rejected materials. Weber et al. (2000) also presented an approach for evaluating the number of suppliers to employ in a procurement situation using MOP and DEA. Talluri et al. (2006) developed a chance-constrained DEA model for selecting suppliers. Talluri and Narasimhan (2003) developed a max-min DEA model for supplier selection problem. Mohammady Garfamy (2006) presented the methodology of applying DEA to compare overall supplier performances based on total cost of ownership (TCO) concept and demonstrated this application through a study for a hypothetical firm.

2.2 *Dual-role factors*

In applying DEA, there is a strong argument for permitting certain factors to simultaneously play the role of both inputs and outputs. Beasley (1990, 1995), in a study of the efficiency of university departments, treated research funding on both the input and output sides. However, as Cook et al. (2006) addressed, the model proposed by Beasley (1990, 1995) has two limitations. The first limitation is that in the absence of constraints (e.g., assurance region or cone-ratio) on the multipliers, each DMU may be 100% efficient. The second limitation is that the dual-role factor is considered differently on the input than on the output side. Cook et al. (2006) developed a new model that has not the above mentioned limitations. Recently, Farzipoor Saen (2010a) proposed a model which can consider multiple dual-role factors for selecting third-party reverse logistics (3PL) providers. In his study, the ratings for service-quality experience and service-quality credence on selecting third-party reverse logistics providers are used as dual-role factors. As well, Farzipoor Saen (2010b) proposed a method for selecting suppliers in the presence of a dual-role factor and weight restrictions. In this study, the R&D cost is considered as both an input and an output.

Recently, Mahdiloo et al. (2011) addressed the problem of a factor in supplier selection analysis which may be classified either an input or an output. They demonstrated the validity of their proposed approach via comparing the results with conventional models. Farzipoor Saen (2010b) and Mahdiloo et al. (2011) used R&D cost of suppliers as a dual-role factor. However, they did not consider non-discretionary inputs.

2.3 *Non-discretionary inputs*

Discretionary models for evaluating the efficiency of suppliers assume that all criteria are discretionary, that is, controlled by the management of each supplier and varied at its discretion. Thus, failure of a supplier to produce maximal output levels with minimal input consumption results in a decreased efficiency score. In any realistic situation, however, there may exist exogenously fixed or non-discretionary criteria that are beyond the control of a management. In an analysis of a network of fast food restaurants, Banker and Morey (1986) illustrated the impact of exogenously determined inputs that are not controllable. In their study, each of the 60 restaurants in the fast food chain consumes six inputs to produce three outputs. The three outputs (all controllable) correspond to breakfast, lunch, and dinner sales. Only two of the six inputs, expenditures for supplies and expenditures for labour, are discretionary. The other four inputs (age of store, advertising level, urban/rural location, and presence/absence of drive-in capability) are beyond the control of the individual restaurant manager. Their analysis clearly demonstrates the value of accounting for the non-discretionary character of these inputs explicitly in the DEA models they employ; the result is identification of a considerably enhanced opportunity for targeted savings in the controllable inputs and targeted increases in the outputs. In the case of supplier selection, distance and supply variety are generally considered as non-discretionary criteria. To select suppliers, Liu et al. (2000) considered supply variety as a non-discretionary output. As well, Farzipoor Saen (2009a) used distance of suppliers from the factory as a non-discretionary input. However, they did not consider dual-role factors in their paper. Recently, Noorizadeh et al. (in press) developed a model to consider dual-role factors, non-discretionary inputs and weight restrictions. Nevertheless, their proposed model can not rank all the suppliers.

2.4 Augmented DEA

While DEA is an appropriate model for supplier evaluation, if the number of inputs and outputs being used increases, the discrimination power of DEA models may decrease. Therefore, in the context of supplier evaluation and selection, DEA may not derive a complete ranking of efficient suppliers. To overcome this problem, Appalla (2003) proposed an augmented DEA, which enhances the capability of discriminating efficient suppliers further by introducing a ‘virtual best’ supplier. Wu et al. (2007) used augmented DEA for supplier ranking which can operate under conditions of imprecise data. As well, Wu and Blackhurst (2009) developed an augmented DEA model which can derive a complete ranking of suppliers. The idea of augmented DEA is based on the introduction of a new virtual DMU called the ‘virtual best’ DMU, which is created by selecting the best values of each criterion from the existing DMU base. This method changes the efficient frontier of the model and thus increases the discriminatory power of the basic DEA model. The efficiency of each DMU is obtained with respect to the efficient frontier of the ‘virtual best’ DMU, which can then be used to rank the DMUs (Wu et al., 2007).

However, all of the above mentioned references which use the concept of virtual best DMU to rank suppliers do not consider dual-role factors and non-discretionary inputs in their research. A technique that can deal with both dual-role factors and non-discretionary inputs in an augmented DEA model is needed to better model such situation.

To the best of knowledge of authors, there is not any reference that discusses suppliers ranking in the presence of both dual-role factors and non-discretionary inputs. The approach presented in this paper has some distinctive contributions.

- Supplier selection is a straightforward process carried out by the proposed model.
- The increasing number of decision-making criteria, complicates the supplier selection process. This paper presents a robust model to solve the multiple-criteria problem.
- The proposed model can be easily computerised, enabling it to serve as a decision-making tool to assist DMs.

- The proposed model does not demand exact weights from the DM. Since classical techniques always require intuitive judgements that have biases, this paper helps DMs to select the suppliers without relying on intuitive judgements.
- The proposed model considers dual-role factors for supplier selection.
- The proposed model considers non-discretionary inputs for supplier selection.
- The proposed model incorporates both dual-role factors and non-discretionary inputs into a single model.
- The proposed model can derive a complete ranking of suppliers.

3 Proposed model

Consider a situation where members k of a set of K DMUs are to be evaluated in terms of R outputs $Y_k = (y_{rk})_{r=1}^{R}$ and I inputs $X_k = (x_{ik})_{i=1}^{I}$. In addition, assume that a particular factor is held by each DMU in the amount w_k, and serves as both an input and output factor. The used nomenclatures in this paper are summarised in Table 1.

Table 1 The nomenclatures

DMU_o	The decision-making unit under investigation
$k = 1, \ldots, K$	Collection of DMUs (suppliers)
$r = 1, \ldots, R$	The set of outputs
$i = 1, \ldots, I$	The set of inputs
I_D	Set of discretionary inputs
I_{ND}	Set of non-discretionary inputs
$f = 1, \ldots, F$	The set of dual-role factors
x_{io}	The i^{th} input of the DMU_o
y_{ro}	The r^{th} output of DMU_o
w_o	Level of dual-role factor of DMU_o
v_{iD}	The weight for i^{th} discretionary input
$\mathrm{v}_{\mathrm{iND}}$	The weight for i^{th} non-discretionary input
u_r	The weight for r^{th} output
x_{ik}	The i^{th} input of DMU_k
y_{rk}	The r^{th} output of DMU_k
w_{fk}	The f^{th} dual-role factor of DMU_k
γ_f	The weight for dual-role factor when it is treated on the output side
β_f	The weight for dual-role factor when it is treated on the input side
$x_{iv\in I_D}$	The i^{th} discretionary input of 'virtual best' DMU
$x_{iv\in I_{ND}}$	The i^{th} non-discretionary input of 'virtual best' DMU
y_{rv}	The r^{th} output of 'virtual best' DMU
w_{fv}	The f^{th} dual-role factor of 'virtual best' DMU

Model (1) is proposed by Cook et al. (2006) for considering a single dual-role factor in DEA.

$$
\begin{aligned}
&\operatorname{Max} \frac{\left(\sum_{r=1}^{R} u_r * y_{ro} + (\gamma - \beta) * w_o\right)}{\left(\sum_{i=1}^{I} v_i * x_{io}\right)} \\
&\text{s.t.} \\
&\frac{\left(\sum_{r=1}^{R} u_r * y_{rk} + (\gamma - \beta) * w_k\right)}{\left(\sum_{i=1}^{I} v_i * x_{ik}\right)} \leq 1, \qquad k = 1, \ldots, K, \\
&u_r, v_i, \gamma, \beta \geq 0
\end{aligned}
\tag{1}
$$

Using a standard technique (see, e.g., Charnes et al., 1978) to transform the above fractional model (1) into a linear model, there will be the following linear programming model.

$$
\begin{aligned}
&\operatorname{Max} \sum_{r=1}^{R} u_r * y_{ro} + (\gamma - \beta) * w_o \\
&\text{s.t.} \\
&\sum_{i=1}^{I} v_i * x_{io} = 1, \\
&\sum_{r=1}^{R} u_r * y_{rk} + (\gamma - \beta) * w_k - \sum_{i=1}^{I} v_i * x_{ik} \leq 0, \qquad k = 1, \ldots, K, \\
&u_r, v_i, \gamma, \beta \geq 0.
\end{aligned}
\tag{2}
$$

To consider multiple dual-role factors in DEA models, Farzipoor Saen (2010a) proposed model (3). Assume that some factors are held by each DMU in the amount w_{fk} ($f = 1, \ldots, F$), and serve as both an input and output factors. The proposed model for considering multiple dual-role factors is as follows:

$$
\begin{aligned}
&\operatorname{Max} \sum_{r=1}^{R} u_r * y_{ro} + \sum_{f=1}^{F} \left(\gamma_f - \beta_f\right) * w_{fo} \\
&\text{s.t.} \\
&\sum_{i=1}^{I} v_i * x_{io} = 1, \\
&\sum_{r=1}^{R} u_r * y_{rk} + \sum_{f=1}^{F} \left(\gamma_f - \beta_f\right) * w_{fk} - \sum_{i=1}^{I} v_i * x_{ik} \leq 0, \qquad k = 1, \ldots, K, \\
&u_r, v_i, \gamma_f, \beta_f \geq 0.
\end{aligned}
\tag{3}
$$

Now, to demonstrate how to incorporate dual-role factors and non-discretionary inputs simultaneously into a single model, model (4) is proposed.

$$\text{Max}\frac{\left(\sum_{r=1}^{R} u_r * y_{ro} + \sum_{f=1}^{F}\left(\gamma_f - \beta_f\right) * w_{fo} - \sum_{i=1}^{I} v_{iND} * x_{io}\right)}{\left(\sum_{i=1}^{I} v_i * x_{io}\right)}$$

s.t.

$$\frac{\left(\sum_{r=1}^{R} u_r * y_{rk} + \sum_{f=1}^{F}\left(\gamma_f - \beta_f\right) * w_{fk} - \sum_{i=1}^{I} v_{iND} * x_{ik}\right)}{\left(\sum_{i=1}^{I} v_i * x_{ik}\right)} \leq 1, \quad k = 1, \ldots, K, \tag{4}$$

$v_{iND}, \beta_f \geq 0,$

$v_{iD}, u_r, \gamma_f \geq \varepsilon,$

$\varepsilon > 0$, (non-Archimedean).

The objective function of the model (4) seeks to maximise the efficiency score of the DMU_o by choosing a set of weights for all discretionary and non-discretionary inputs, outputs and dual-role factors. The first constraint set of model (4) ensures that, under the set of chosen weights, the efficiency scores of all DMUs are less than or equal to 1. Other constraint sets of model (4) guarantee the non-negativity of all weights. Since we want to maximise the ratio, the way to achieve that goal is decreasing the denominator; therefore, the model suggests that inputs should be decreased. Outcome of model (4) is an efficiency score equal to one for efficient DMUs and less than one for inefficient DMUs. Model (4) can be converted into a linear programming problem as follows:

$$\text{Max} \sum_{r=1}^{R} u_r * y_{ro} + \sum_{f=1}^{F}\left(\gamma_f - \beta_f\right) * w_{fo} - \sum_{i=1}^{I} v_{iND} * x_{io}$$

s.t.

$$\begin{aligned}
&\sum_{i=1}^{I} v_{iD} * x_{io} = 1,\\
&\sum_{r=1}^{R} u_r * y_{rk} + \sum_{f=1}^{F}\left(\gamma_f - \beta_f\right) * w_{fk}\\
&\quad -\left(\sum_{i \in I_D}^{I} v_{iD} * x_{ik} + \sum_{i \in I_{ND}}^{I} v_{iND} * x_{ik}\right) \leq 0, \quad k = 1, \ldots, K,\\
&v_{iND}, \beta_f \geq 0,\\
&v_{iD}, u_r, \gamma_f \geq \varepsilon,\\
&\varepsilon > 0, \text{ (non-Archimedean).}
\end{aligned} \tag{5}$$

Now, one of three possibilities exists in regard to the sign of $\hat{\gamma} - \hat{\beta}$, where $\hat{\gamma}, \hat{\beta}$ are the optimal values from model (3); $\hat{\gamma} - \hat{\beta} > 0, = 0,$ or < 0 (Cook et al., 2006).

Case 1 If $\hat{\gamma} - \hat{\beta} < 0$, then the dual-role factor is 'behaving like input'. Hence, less of this factor is better, and would lead to an increase in efficiency.

Case 2 If $\hat{\gamma} - \hat{\beta} > 0$, then the dual-role factor is 'behaving like output'. Hence, more of this factor is better, and would lead to an increase in efficiency.

Case 3 If $\hat{\gamma} - \hat{\beta} = 0,$ then dual-role factor is at equilibrium level.

However, efficiency scores calculated by model (5) can not give a complete ranking of suppliers. To derive a complete ranking, a 'virtual best' DMU is incorporated into model (5). Therefore, model (6) is an augmented DEA model which considers both dual-role factors and non-discretionary inputs.

$$
\begin{aligned}
&\operatorname{Max} \sum\nolimits_{r=1}^{R} u_r * y_{ro} + \sum\nolimits_{f=1}^{F} \left(\gamma_f - \beta_f\right) * w_{fo} - \sum\nolimits_{i=1}^{I} v_{iND} * x_{io} \\
&\text{s.t.} \\
&\sum\nolimits_{i=1}^{I} v_{iD} * x_{io} = 1, \\
&\sum\nolimits_{r=1}^{R} u_r * y_{rk} + \sum\nolimits_{f=1}^{F} \left(\gamma_f - \beta_f\right) * w_{fk} \\
&\quad -\left(\sum\nolimits_{i \in I_D}^{I} v_{iD} * x_{ik} + \sum\nolimits_{i \in I_{ND}}^{I} v_{iND} * x_{ik}\right) \le 0, \quad k = 1, \ldots, K, \\
&\sum\nolimits_{r=1}^{R} u_r * y_{rv} + \sum\nolimits_{f=1}^{F} \left(\gamma_f - \beta_f\right) * w_{fv} \\
&\quad -\left(\sum\nolimits_{i \in I_D}^{I} v_{iD} * x_{iv} + \sum\nolimits_{i \in I_{ND}}^{I} v_{iND} * x_{iv}\right) \le 0 \\
&v_{iND}, \beta_f \ge 0, \\
&v_{iD}, u_r, \gamma_f \ge \varepsilon, \\
&\varepsilon > 0, \text{(non-Archimedean).}
\end{aligned}
\tag{6}
$$

Note that, model (6) is applied only for selecting a supplier from efficient suppliers and resulting of this model is less than 1 for efficient DMUs. The amount of discretionary and non-discretionary inputs, outputs and dual-role factors associated with the 'virtual best' supplier is created in the following form.

$$
\begin{aligned}
&y_{rv} = \max\left(y_{rk}\right), r = 1, \ldots, R, && k \in \text{efficient DMUs} \\
&x_{iv \in I_D} = \min\left(x_{ik}\right), i \in I_D, && k \in \text{efficient DMUs} \\
&x_{iv \in I_{ND}} = \min\left(x_{ik}\right), i \in I_{ND}, && k \in \text{efficient DMUs} \\
&w_{fv} = \max\left(w_{fk}\right), f = 1, \ldots, F, && k \in \text{efficient DMUs, when dual-role} \\
& && \text{factor is treated on the output side} \\
&\mathrm{w}_{fv} = \min\left(w_{fk}\right), f = 1, \ldots, F, && k \in \text{efficient DMUs, when dual-role} \\
& && \text{factor is treated on the input side.}
\end{aligned}
$$

4 Numerical example

In order to demonstrate the application of the proposed approach in supplier selection context, the dataset for this study is partially taken from Farzipoor Saen (2010b). The inputs for selecting suppliers include total cost of shipments (TC), number of shipments per month (NS), and R&D cost. The outputs utilised in the study are number of shipments to arrive on time (NOT), number of bills received from the supplier without errors (NB), product quality (PQ), and R&D. R&D plays the role of both input and output. Distance (D) is considered as a non-discretionary input. Table 2 shows the dataset for 18 suppliers.

Table 2 Dataset for 18 suppliers

Supplier no.	*TC (1,000\$)*	*NS*	*D (km)*	*R&D (1,000\$)*	*NOT*	*NB*	*PQ*[1]
1	253	197	249	20	187	90	1
2	268	198	643	32	194	130	5
3	259	229	714	15	220	200	3
4	180	169	1809	10	160	100	4
5	257	212	238	16	204	173	1
6	248	197	241	28	192	170	2
7	272	209	1404	12	194	60	5
8	330	203	984	36	195	145	3
9	327	208	641	30	200	150	2
10	330	203	588	28	171	90	3
11	321	207	241	19	174	100	1
12	329	234	567	25	209	200	2
13	281	173	567	18	165	163	1
14	309	203	967	27	199	170	4
15	291	193	635	22	188	185	2
16	334	177	795	31	168	85	3
17	249	185	689	50	177	130	5
18	216	176	913	15	167	160	4

Notes: [1]This variable is a qualitative criterion. Assume that for this qualitative variable each supplier is rated on a 5-point Likert scale, where the particular point on the scale is chosen through a consensus on the part of executives within the organisation. 5-point scales are common for evaluating in terms of qualitative data, and are often accompanied by interpretations such as: 1 = very bad, 2 = bad, 3 = medium, 4 = good, 5 = very good, which are easily understood by DM.

Table 3 reports the results of efficiency score obtained by model (5). Also, the behaviour of dual-role factor for 18 suppliers is depicted in this table. Model (5) identified suppliers 2, 3, 4, 5, 6, 7, 14, 15, 17, and 18 to be efficient with a relative efficiency score of 1. The remaining 8 suppliers with relative efficiency score of less than 1 are considered to be inefficient. Note that, each DEA model seeks to determine which of the *n* DMUs define an envelopment surface that represents best practice, referred to as the empirical production function or the efficient frontier. DMUs that lie on the surface are deemed efficient in DEA, while those DMUs that do not, are termed inefficient. DEA provides a comprehensive analysis of relative efficiencies for multiple input-multiple output situations by evaluating each DMU and measuring its performance relative to an envelopment surface composed of other DMUs (Farzipoor Saen, 2009b). In order to interpret the behaviour of dual-role factor, consider, for instance, suppliers 1 and 2. For supplier 1, with a negative $\hat{\gamma}_1 - \hat{\beta}_1$, R&D is behaving like an input, and lower value of such factor would increase the efficiency of the supplier. For supplier 2, with a positive $\hat{\gamma}_1 - \hat{\beta}_1$, R&D is behaving like an output, and higher level of such factor would improve the efficiency of the supplier.

Table 3 Efficiency scores and output/input behaviour using model (5)

Supplier no.	*Efficiency scores in the presence of both dual-role factor and non-discretionary input*	$\hat{\gamma}_1$	$\hat{\beta}_1$	$\hat{\gamma}_1 - \hat{\beta}_1$
1	0.9728	0.0001	0.001072786	–0.000972786
2	1	0.000981117	0	0.000981117
3	1	0.0001	0.000758839	–0.000658839
4	1	0.0001	0.09193314	–0.09183314
5	1	0.0001	0.001004062	–0.000904062
6	1	0.000882344	0	0.000882344
7	1	0.0001	0.006941042	–0.006841042
8	0.9807	0.000923908	0	0.000923908
9	0.9776	0.000196352	0	0.000196352
10	0.8524	0.000164275	0	0.000164275
11	0.8574	0.0001	0.0010197	–0.0009197
12	0.9291	0.0001	0.003157961	–0.003057961
13	0.9977	0.0001	0.01230339	–0.01220339
14	1	0.000234812	0	0.000234812
15	1	0.007871516	0	0.007871516
16	0.9603	0.001106689	0	0.001106689
17	1	0.004458744	0	0.004458744
18	1	0.006624602	0	0.006624602

Now, we analyse the effects of considering ‘D’ as a non-discretionary input on the results. Therefore, we re-solve the problem by considering ‘D’ as a discretionary factor. The results are shown in Table 4. In this time, 9 out of 18 suppliers are efficient. By comparing Tables 3 and 4, it can be seen that the ranking of some suppliers by two strategies (considering distance as a non-discretionary or discretionary factor) are different.

The problem now becomes selecting a supplier from those ten efficient suppliers (when distance is considered as a non-discretionary input). Therefore, we use model (6) to derive the suppliers’ score and their complete ranking. The scores derived by using model (6) and final ranking of suppliers have been displayed in Table 5. As Table 5 shows, supplier 17 receives the highest score in the presence of virtual best DMU, and is the first candidate for selection. If they are able to use the minimum inputs to produce the maximum outputs, they are DEA efficient; otherwise, they are inefficient. Therefore, DM can choose one or more of these efficient suppliers. Samples of models (5) and (6) for supplier 2 have been presented in Appendix. ε has been set to be 0.0001.

Table 4 Efficiency scores when 'D' is treated as a discretionary input

Supplier no.	*Efficiency*
1	0.9711
2	1
3	1
4	1
5	1
6	1
7	1
8	0.9236
9	0.9416
10	0.8410
11	0.8606
12	0.9375
13	0.9973
14	0.9817
15	1
16	0.9236
17	1
18	1

Table 5 Efficiency scores and ranking of efficient suppliers in the presence of virtual best DMU

Rank	*Supplier no.*	*Efficiency scores obtained by model (6)*
1	17	0.8975
2	2	0.8373
3	15	0.7988
4	4	0.7894
5	7	0.7842
6	18	0.7626
7	6	0.7436
8	14	0.7431
9	3	0.7332
10	5	0.7322

5 Concluding remarks

Today, manufacturing companies are facing intense global competition and consequently an incredible pressure to reduce the cost and development time of a new product. It is well known that a substantial proportion of the cost of a typical engineering product is accounted for in raw material, components and other supplies; on average, manufacturers' purchases of goods and services amounts to 55% of revenue (Akarte et al., 2001). Purchasing is thus one of the most crucial and vital activities of business, as it has a significant impact on finance, operations and competitiveness of the organisation (Stainer et al., 1996).

This paper has provided a model for selecting suppliers in the presence of both dual-role factors and non-discretionary inputs.

The problem considered in this study is at the initial stage of investigation and further researches can be done based on the results of this paper. Some of them are as below:

- Similar research can be repeated for supplier selection in the presence of fuzzy data.
- Preferences of DM can be incorporated into the proposed algorithm by restricting the feasible region of the inputs and outputs' weights.
- Similar research can be repeated in the presence of stochastic data.

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Appendix

Model (5) for supplier #2:

$$
\begin{aligned}
&\text{M ax} = 194*u_1 + 130*u_2 + 1*u_3 + 32*\gamma_1 - 32*\beta_1 - 643*v_{1ND},\\
&\text{s.t.}\quad 268*v_{1D} + 198*v_{2D} = 1,\\
&187*u_1 + 90*u_2 + 1*u_3 + 20*\gamma_1 - \left(253*v_{1D} + 197*v_2 D + 20*\beta_1 + 249*v_{1ND}\right) \le 0,\\
&194*u_1 + 130*u_2 + 5*u_3 + 32*\gamma_1 - \left(268*v_{1D} + 198*v_{2D} + 32*\beta_1 + 643*v_{1ND}\right) \le 0,\\
&220*u_1 + 200*u_2 + 3*u_3 + 15*\gamma_1 - \left(259*v_{1D} + 229*v_{2D} + 15*\beta_1 + 714*v_{1ND}\right) \le 0,\\
&160*u_1 + 100*u_2 + 4*u_3 + 10*\gamma_1 - \left(180*v_{1D} + 169*v_{2D} + 10*\beta_1 + 1{,}809*v_{1ND}\right) \le 0,\\
&204*u_1 + 173u_2 + 1*u_3 + 16*\gamma_1 - \left(257*v_{1D} + 212*v_{2D} + 16*\beta_1 + 238*_{1ND}\right) \le 0,\\
&192*u_1 + 170*u_2 + 2*u_3 + 28*\gamma_1 - \left(248*v_{1D} + 197*v_{2D} + 28*\beta_1 + 241*v_{1ND}\right) \le 0,\\
&194*u_1 + 60*u_2 + 5*u_3 + 12*\gamma_1 - \left(272*v_{1D} + 209*v_{2D} + 12*\beta_1 + 1{,}404*v_{1ND}\right) \le 0,\\
&195*u_1 + 145*u_2 + 3*u_3 + 36*\gamma_1 - \left(330*v_{1D} + 203*v_{2D} + 36*\beta_1 + 984*v_{1ND}\right) \le 0,\\
&200*u_1 + 150*u_2 + 2*u_3 + 30*\gamma_1 - \left(327*v_{1D} + 208*v_{2D} + 30*\beta_1 + 641*v_{1ND}\right) \le 0,\\
&171*u_1 + 90*u_2 + 3*u_3 + 28*\gamma_1 - \left(330*v_{1D} + 203*v_{2D} + 28*\beta_1 + 588*v_{1ND}\right) \le 0,\\
&174*u_1 + 100*u_2 + 1*u_3 + 19*\gamma_1 - \left(231*v_{1D} + 207*v_{2D} + 19*\beta_1 + 241*v_{1ND}\right) \le 0,\\
&209*u_1 + 200*u_2 + 2*u_3 + 25*\gamma_1 - \left(329*v_{1D} + 324*v_{2D} + 25*\beta_1 + 567*v_{1ND}\right) \le 0,\\
&165*u_1 + 163*u_2 + 1*u_3 + 18*\gamma_1 - \left(281*v_{1D} + 173*v_{2D} + 18*\beta_1 + 567*v_{1ND}\right) \le 0,\\
&199*u_1 + 170*u_2 + 4*u_3 + 27*\gamma_1 - \left(309*v_{1D} + 203*v_{2D} + 27*\beta_1 + 967*v_{1ND}\right) \le 0,\\
&188*u_1 + 185*u_2 + 2*u_3 + 22*\gamma_1 - \left(291*v_{1D} + 193*v_{2D} + 22*\beta_1 + 635*v_{1ND}\right) \le 0,\\
&168*u_1 + 85*u_2 + 3*u_3 + 31*\gamma_1 - \left(334*v_{1D} + 177*v_{2D} + 31*\beta_1 + 795*v_{1ND}\right) \le 0,\\
&177*u_1 + 130*u_2 + 5*u_3 + 50*\gamma_1 - \left(249*v_{1D} + 185*v_{2D} + 50*\beta_1 + 689*v_{1ND}\right) \le 0,\\
&167*u_1 + 160*u_2 + 4*u_3 + 15*\gamma_1 - \left(216*v_{1D} + 176*v_{2D} + 15*\beta_1 + 913*v_{1ND}\right) \le 0,\\
&v_{1D} \ge 0.0001,\\
&v_{2D} \ge 0.0001,\\
&u_1 \ge 0.0001,\\
&u_2 \ge 0.0001,\\
&u_3 \ge 0.0001,\\
&\gamma_1 \ge 0.0001,\\
&\beta_1 \ge 0,\\
&v_{1ND} \ge 0.
\end{aligned}
$$

Model (6) for supplier #2:

$$\text{Max} = 194*u_1 + 130*u_2 + 1*u_3 + 32*\gamma_1 - 32*\beta_1 - 643*v_{1ND},$$
$$\text{s.t.} \quad 268*v_{1D} + 198*v_{2D} = 1,$$
$$187*u_1 + 90*u_2 + 1*u_3 + 20*\gamma_1 - (253*v_{1D} + 197*v_2 D + 20*\beta_1 + 249*v_{1ND}) \le 0,$$
$$194*u_1 + 130*u_2 + 5*u_3 + 32*\gamma_1 - (268*v_{1D} + 198*v_{2D} + 32*\beta_1 + 643*v_{1ND}) \le 0,$$
$$220*u_1 + 200*u_2 + 3*u_3 + 15*\gamma_1 - (259*v_{1D} + 229*v_{2D} + 15*\beta_1 + 714*v_{1ND}) \le 0,$$
$$160*u_1 + 100*u_2 + 4*u_3 + 10*\gamma_1 - (180*v_{1D} + 169*v_{2D} + 10*\beta_1 + 1{,}809*v_{1ND}) \le 0,$$
$$204*u_1 + 173u_2 + 1*u_3 + 16*\gamma_1 - (257*v_{1D} + 212*v_{2D} + 16*\beta_1 + 238*_{1ND}) \le 0,$$
$$192*u_1 + 170*u_2 + 2*u_3 + 28*\gamma_1 - (248*v_{1D} + 197*v_{2D} + 28*\beta_1 + 241*v_{1ND}) \le 0,$$
$$194*u_1 + 60*u_2 + 5*u_3 + 12*\gamma_1 - (272*v_{1D} + 209*v_{2D} + 12*\beta_1 + 1{,}404*v_{1ND}) \le 0,$$
$$195*u_1 + 145*u_2 + 3*u_3 + 36*\gamma_1 - (330*v_{1D} + 203*v_{2D} + 36*\beta_1 + 984*v_{1ND}) \le 0,$$
$$200*u_1 + 150*u_2 + 2*u_3 + 30*\gamma_1 - (327*v_{1D} + 208*v_{2D} + 30*\beta_1 + 641*v_{1ND}) \le 0,$$
$$171*u_1 + 90*u_2 + 3*u_3 + 28*\gamma_1 - (330*v_{1D} + 203*v_{2D} + 28*\beta_1 + 588*v_{1ND}) \le 0,$$
$$174*u_1 + 100*u_2 + 1*u_3 + 19*\gamma_1 - (231*v_{1D} + 207*v_{2D} + 19*\beta_1 + 241*v_{1ND}) \le 0,$$
$$209*u_1 + 200*u_2 + 2*u_3 + 25*\gamma_1 - (329*v_{1D} + 324*v_{2D} + 25*\beta_1 + 567*v_{1ND}) \le 0,$$
$$165*u_1 + 163*u_2 + 1*u_3 + 18*\gamma_1 - (281*v_{1D} + 173*v_{2D} + 18*\beta_1 + 567*v_{1ND}) \le 0,$$
$$199*u_1 + 170*u_2 + 4*u_3 + 27*\gamma_1 - (309*v_{1D} + 203*v_{2D} + 27*\beta_1 + 967*v_{1ND}) \le 0,$$
$$188*u_1 + 185*u_2 + 2*u_3 + 22*\gamma_1 - (291*v_{1D} + 193*v_{2D} + 22*\beta_1 + 635*v_{1ND}) \le 0,$$
$$168*u_1 + 85*u_2 + 3*u_3 + 31*\gamma_1 - (334*v_{1D} + 177*v_{2D} + 31*\beta_1 + 795*v_{1ND}) \le 0,$$
$$177*u_1 + 130*u_2 + 5*u_3 + 50*\gamma_1 - (249*v_{1D} + 185*v_{2D} + 50*\beta_1 + 689*v_{1ND}) \le 0,$$
$$167*u_1 + 160*u_2 + 4*u_3 + 15*\gamma_1 - (216*v_{1D} + 176*v_{2D} + 15*\beta_1 + 913*v_{1ND}) \le 0,$$
$$220*u_1 + 200*u_2 + 5*u_3 + 50*\gamma_1 - (180*v_{1D} + 169*v_{2D} + 10*\beta_1 + 238*v_{1ND}) \le 0,$$
$$v_{1D} \ge 0.0001,$$
$$v_{2D} \ge 0.0001,$$
$$u_1 \ge 0.0001,$$
$$u_2 \ge 0.0001,$$
$$u_3 \ge 0.0001,$$
$$\gamma_1 \ge 0.0001,$$
$$\beta_1 \ge 0,$$
$$v_{1ND} \ge 0.$$